



Probabilistic Reachable Set Estimation for Uncertain Systems with Saturating Inputs

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Introduction

Problem Setup and Stochastic Tubes

Given discrete-time LTI dynamics:

$$x_{k+1} = Ax_k + Bu_k + w_k$$

Noise Characteristics

Unbounded, i.i.d., with:

$$\mathbb{E}[w_k] = 0, \quad \mathbb{E}[w_k^\top w_k] = W.$$

Constraints

$$\Pr\{x \in \mathcal{X}\} \geq 1 - \varepsilon_x,$$

$$\Pr\{u \in \mathcal{U}\} \geq 1 - \varepsilon_u.$$

- Parameterize $u_k = v_k + Ke_k$, decompose $x_k = z_k + e_k$, such that:
MPC
action

$$z_{k+1} = Az_k + Bv_k, \quad e_{k+1} = (A + BK)e_k + w_k,$$

- Impose $z \in \mathcal{X} \ominus \mathcal{R}_e$ and $v \in \mathcal{U} \ominus K\mathcal{R}_e$.
probabilistic
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- Impose $z \in \mathcal{X} \ominus \mathcal{R}_e$ and $v \in \mathcal{U} \ominus K\mathcal{R}_e$.

Actuator saturation occurs for any $u \notin \mathcal{U}$!

Objectives

Our goal is to maintain the stochastic tubes approach for its efficient closed-loop implementation while:

1. Guaranteeing state chance constraints (deterministic under some tightening, i.e. $z \in \mathcal{X} \ominus \mathcal{R}_e$).
2. Enforcing hard input constraints in the presence of **unbounded noise**.
3. Minimizing the conservatism of \mathcal{R}_e .

Main Focus

We need a suitable synthesis of Probabilistic Reachable Sets \mathcal{R}_e .

Methodology

Our Proposal

- Hard input constraints can be enforced by saturating the control:

$$x_{k+1} = Ax_k + B\varphi(u_k) + w_k$$

↑
component-wise saturation function

- Following the same stochastic tubes approach, we get:

$$z_{k+1} = Az_k + Bv_k \quad e_{k+1} = \underbrace{Ae_k + B(\varphi(v_k + Ke_k) - v_k)}_{f(e_k, v_k)} + w_k$$

↑
Open-loop stable

$f(e_k, v_k)$ is nonlinear and dependent on v . How do we construct PRS?

Main Idea

Construct a linear bound on $f(e_k, v_k)$ valid for any admissible v .

Handling Saturations

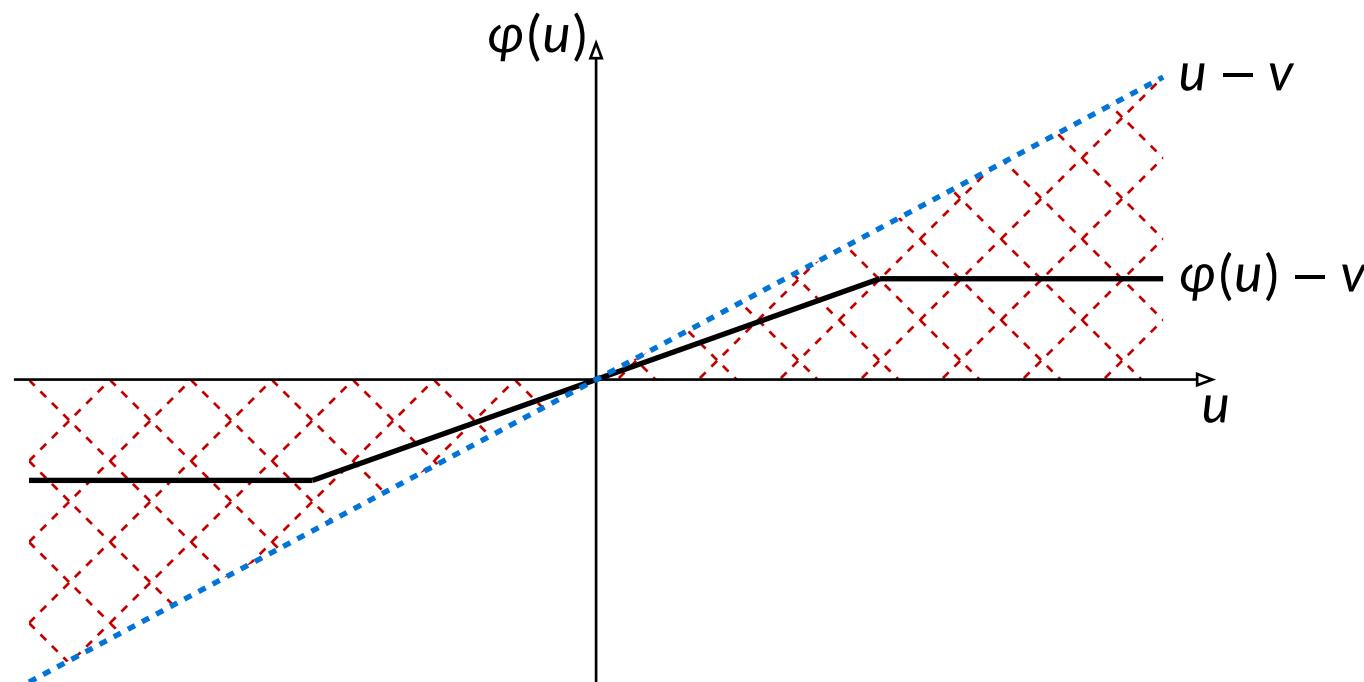
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$$\begin{cases} 0 \leq \varphi(K_i e + v_i) - v_i \leq K_i e & \text{if } K_i e \geq 0 \\ K_i e \leq \varphi(K_i e + v_i) - v_i \leq 0 & \text{if } K_i e < 0 \end{cases}$$



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3. Replace the nonlinearity with a convex representation.

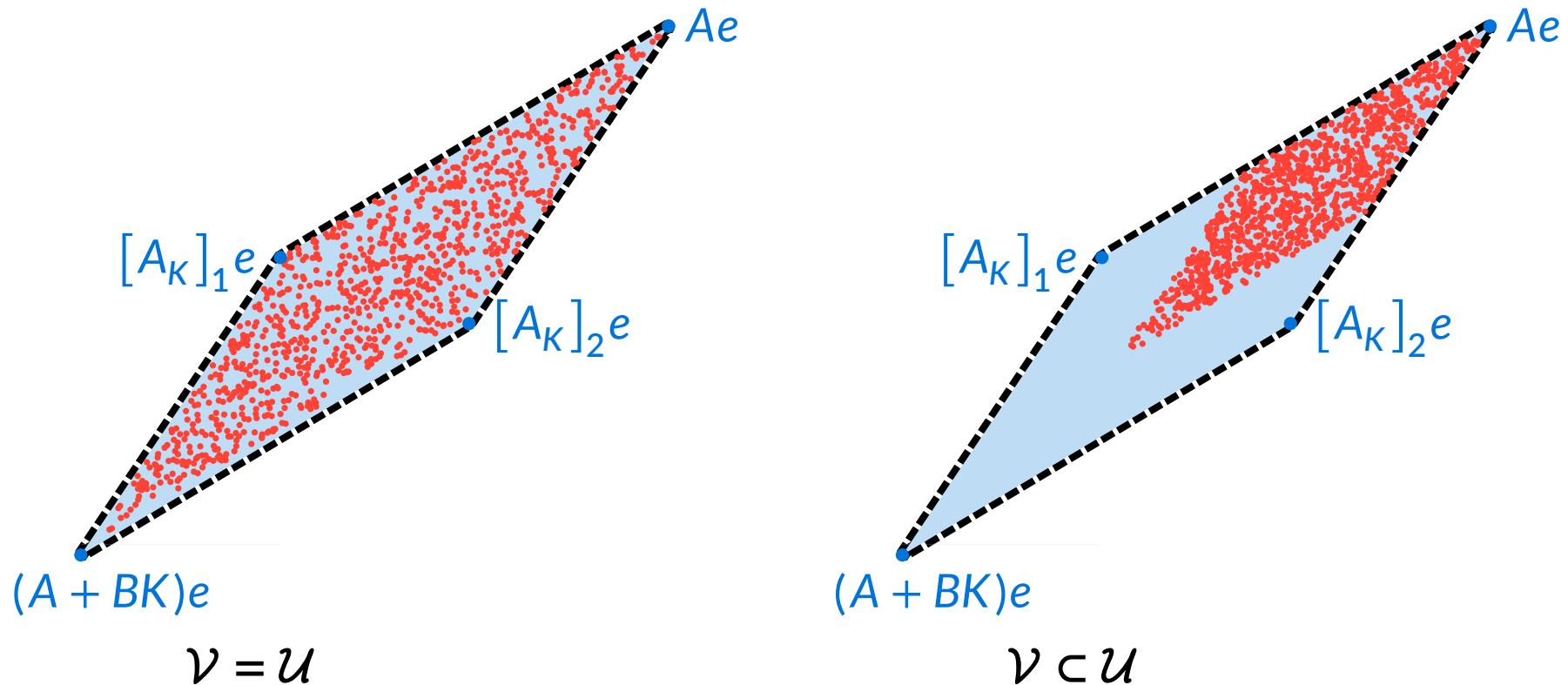
$$f(e, v) \in \text{co} \left\{ \left(A + \sum_{i \in \mathcal{J}} B_{(i)} K_i \right) e \right\}_{\mathcal{J} \subseteq \mathbb{N}^m}$$

$[A_K]_i$

**$f(e, v)$ is bounded from all sides by a convex polytope
encoding different saturation scenarios!**

A Visual Representation of the Convex Bound

For some e , and any $v \in \mathcal{V}$, the bound holds with varying degree of conservatism. For $m = 2$:



Contracting Dynamics

1

Linear System Contraction (open-loop)

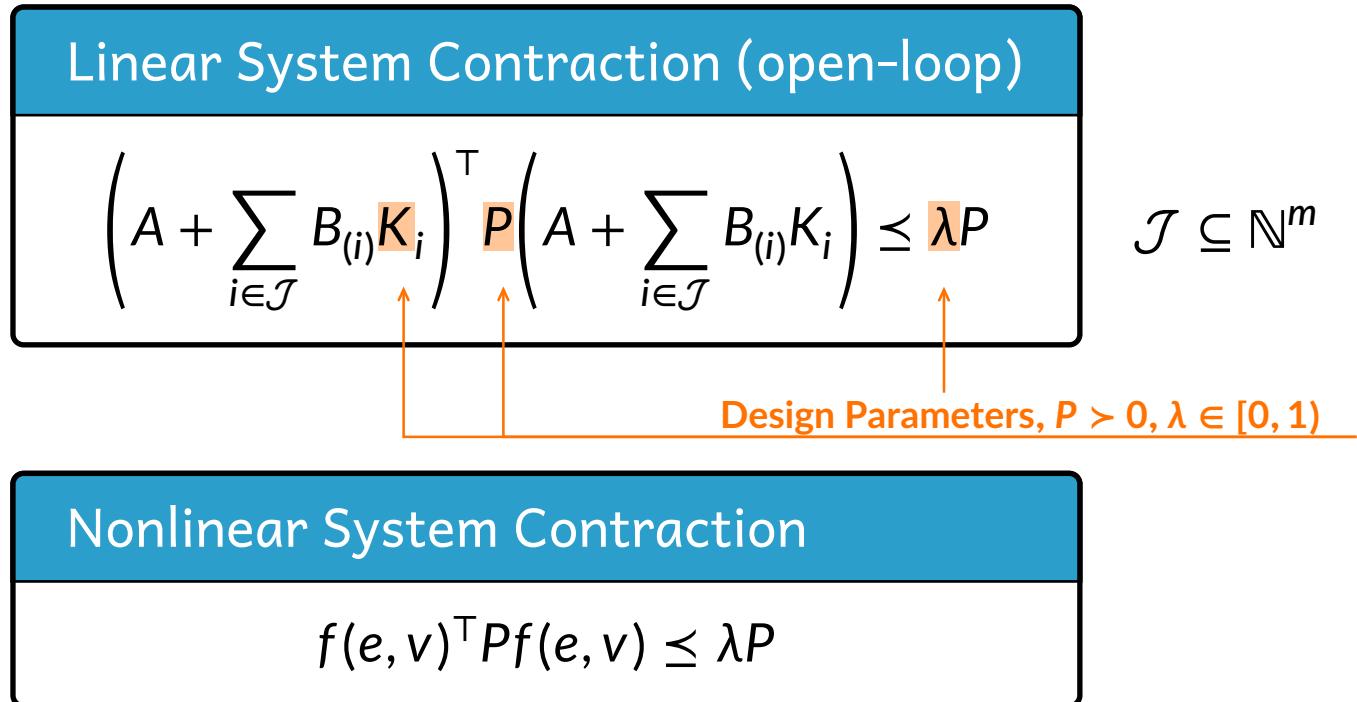
$$\left(A + \sum_{i \in \mathcal{J}} B_{(i)} K_i \right)^T P \left(A + \sum_{i \in \mathcal{J}} B_{(i)} K_i \right) \leq \lambda P$$

$$\mathcal{J} \subseteq \mathbb{N}^m$$

Design Parameters, $P > 0, \lambda \in [0, 1]$

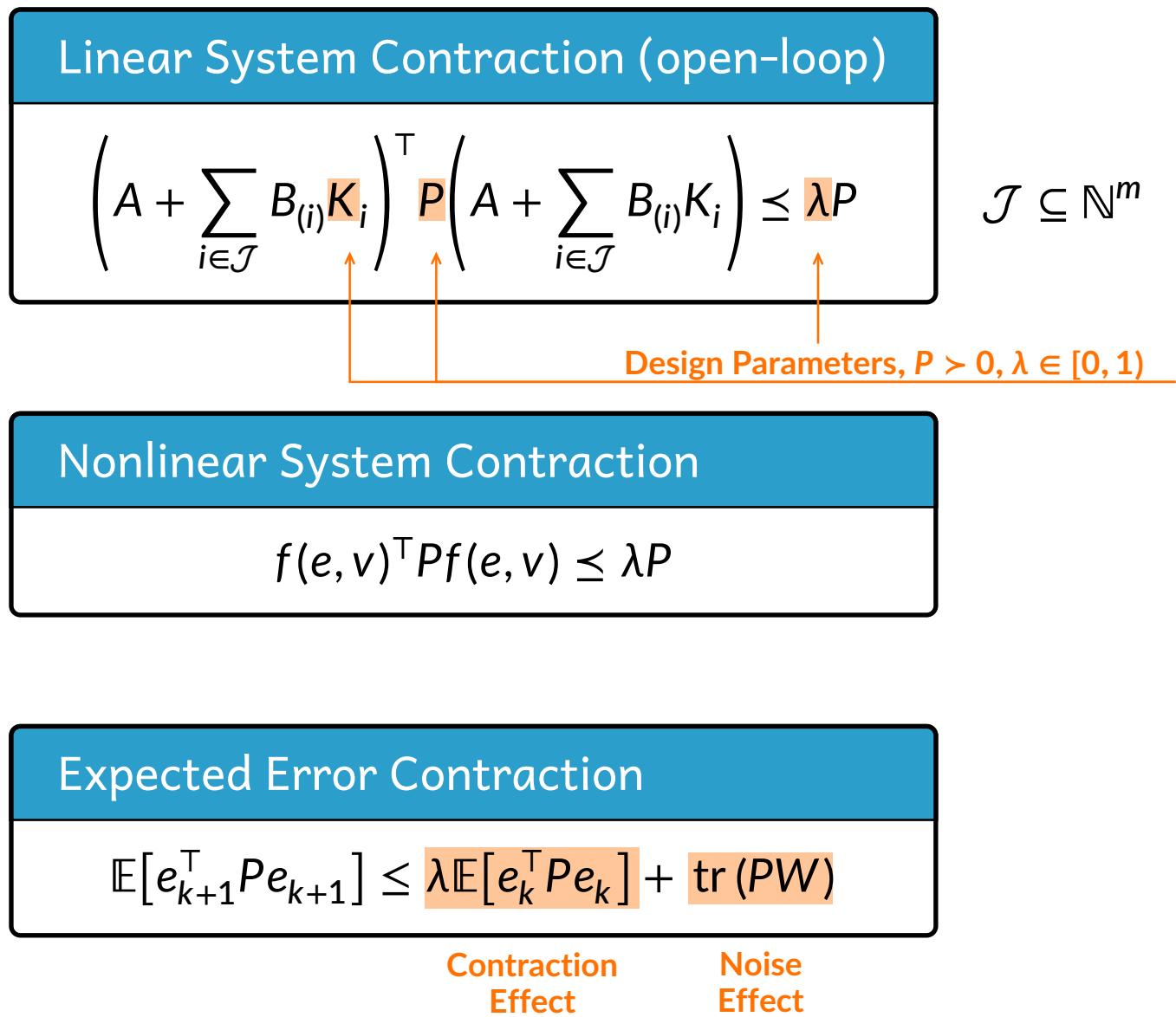
Contracting Dynamics

- 1
via
bound



Contracting Dynamics

- 1 via bound
- 2 incorporate noise
- 3



Constructing Reachable Sets

4

Closed-form Bound on Expectation

$$\mathbb{E}[e_k^\top P e_k] \leq \frac{1 - \lambda^k}{1 - \lambda} \text{tr}(PW) \leq \frac{1}{1 - \lambda} \text{tr}(PW)$$

Constructing Reachable Sets

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Markov
inequality

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Probabilistic Reachable Set (PRS)

$$\mathcal{R}_k^{\varepsilon_x}(\lambda) : \left\{ e \mid e^\top P e \leq \frac{1 - \lambda^k}{\varepsilon_x(1 - \lambda)} \text{tr}(PW) \right\}$$

Constructing Reachable Sets

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5

taking lim
as $k \rightarrow \infty$

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6

Probabilistic Ultimate Bound (PUB)

$$\mathcal{R}_\infty^{\varepsilon_x}(\lambda) : \left\{ e \mid e^\top Pe \leq \frac{1}{\varepsilon_x(1 - \lambda)} \text{tr}(PW) \right\}$$

Reducing Conservatism

Open-loop Contraction

- λ is a conservative contraction rate leading to very loose bounds.

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Intuition

$$\left(A + \sum_{i \in \mathcal{J}} B_{(i)} K_i \right)^T P \left(A + \sum_{i \in \mathcal{J}} B_{(i)} K_i \right) \leq \lambda P$$

is equivalent to:

$$A^T P A \leq \lambda P \quad \text{Limiting Constraint}$$

$$\left(A + B_{(1)} K_1 \right)^T P \left(A + B_{(1)} K_1 \right) \leq \lambda P$$

⋮

$$\left(A + B_{(1:2)} K_{1:2} \right)^T P \left(A + B_{(1:2)} K_{1:2} \right) \leq \lambda P$$

⋮

$$(A + BK)^T P (A + BK) \leq \lambda P$$

Open-loop Contraction

- λ is a conservative contraction rate leading to very loose bounds.
⇒ sets don't take into account the stabilizing effect of feedback.

We can do better!

When $\varphi(u) = u$, a stronger contraction $\lambda_L \leq \lambda$ holds for the already computed K, P .

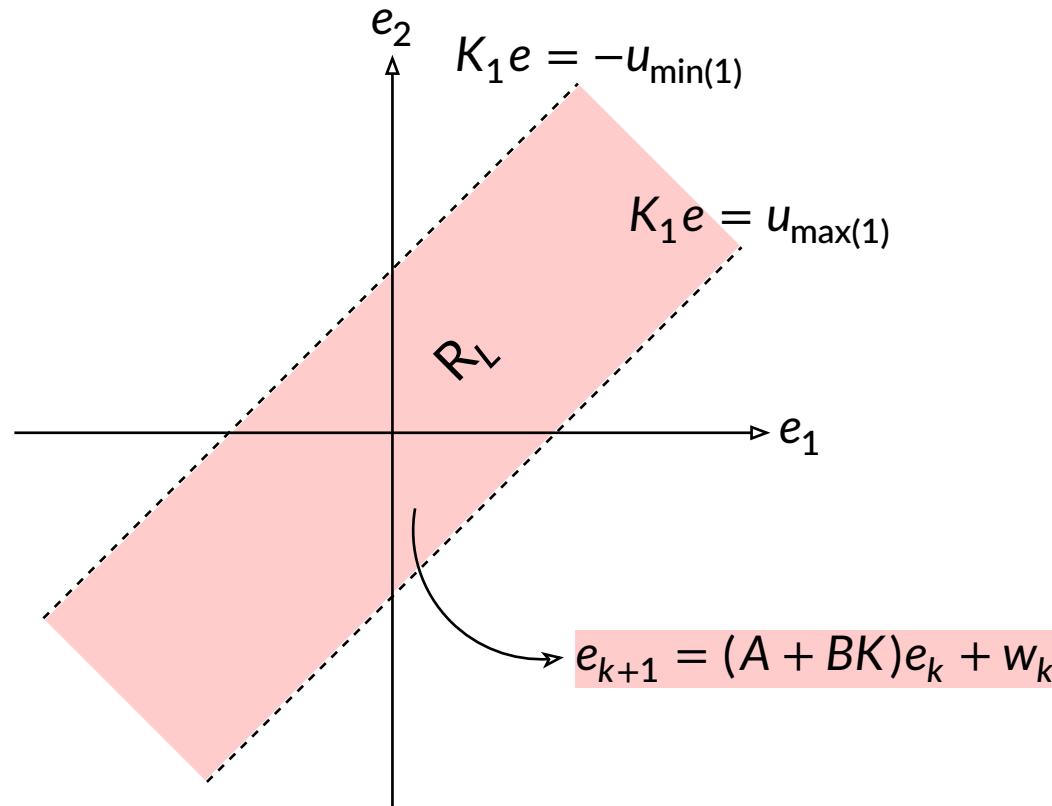
$$(A + BK)^T P (A + BK) \leq \lambda_L P$$

$$\mathbb{E}[e_{k+1}^T P e_{k+1}] \leq \lambda_L \mathbb{E}[e_k^T P e_k] + \text{tr}(P W)$$

How can we account for this contraction in our analysis?

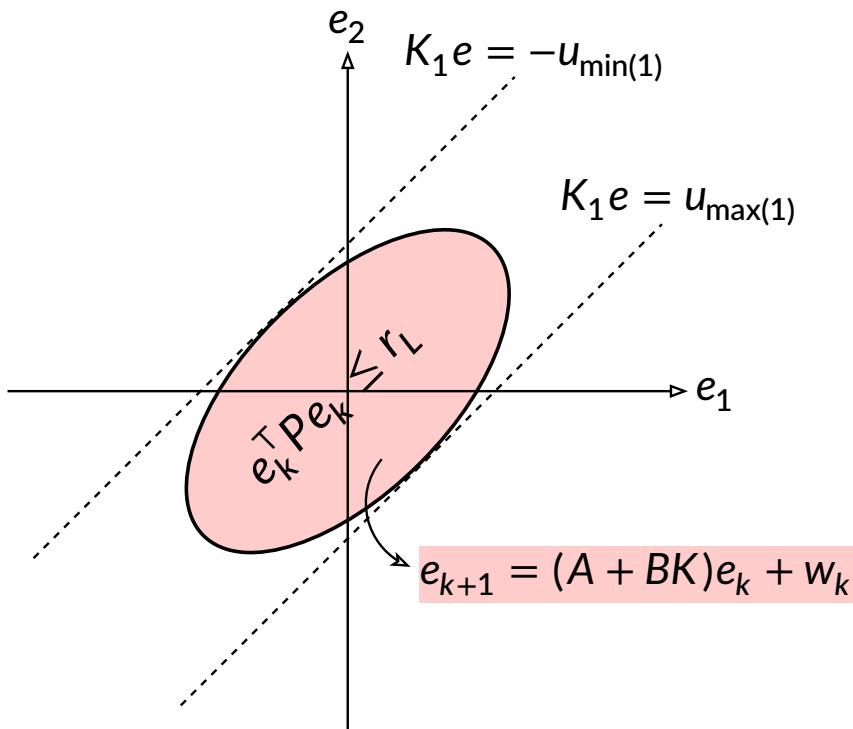
Saturation Region of Linearity

The system does not saturate ($\varphi(u) = u$) when we are in its region of linearity. R_L is the true polyehdral region of linearity. It may be unbounded in certain (unconstrained) directions.



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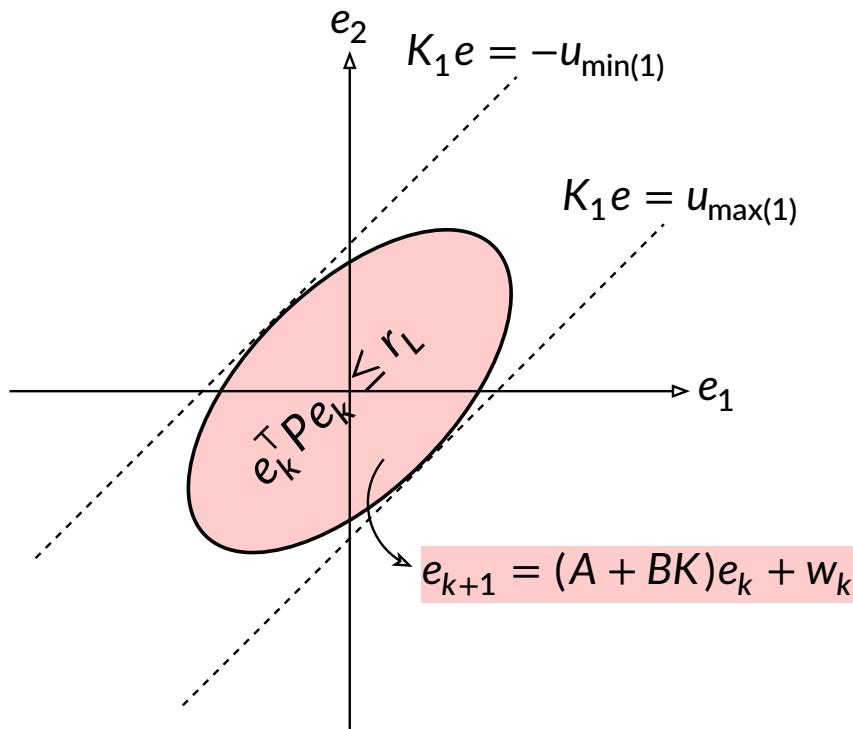
Ellipsoidal Region of Linearity

R_L can be under-approximated by an ellipsoid with:

- shape matrix P .
- scaling r_L , that grows with the energy allocated to the feedback Ke .

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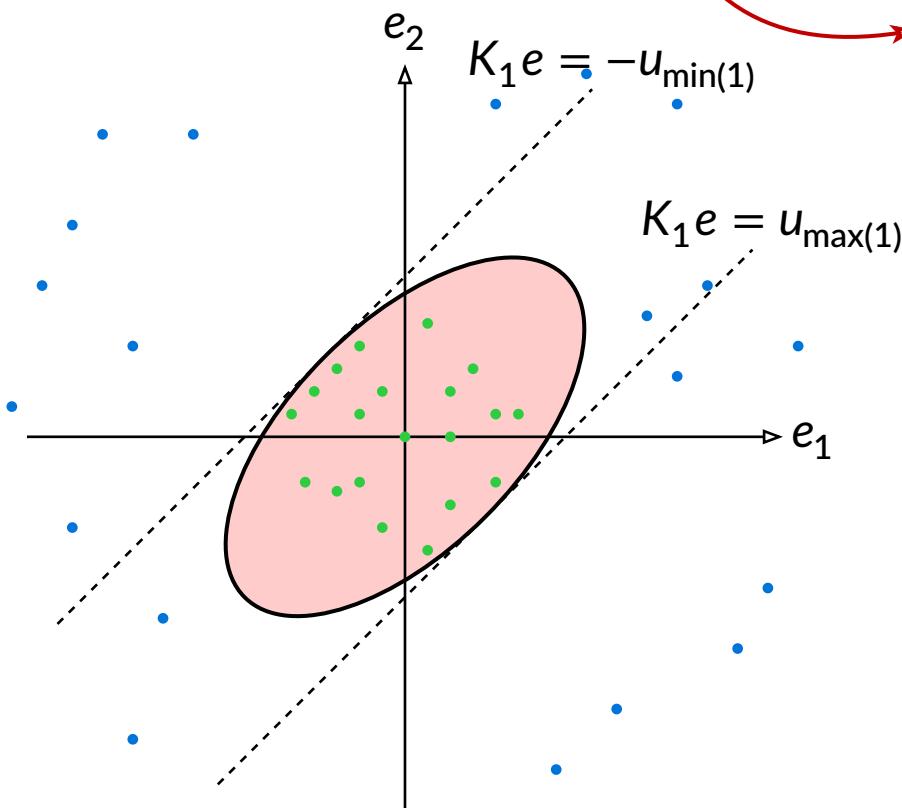
- shape matrix P .
- scaling r_L , that grows with the energy allocated to the feedback Ke .

How can we integrate this into our bound?

Weighted Bound on the Error

Main Idea

The system probabilistically switches between **saturated** and **unsaturated** modes.



Can we characterize this?

Use Markov inequality:

$$\Pr\{e_k^T P e_k \leq r_L\} \geq 1 - \frac{E[e_k^T P e_k]}{r_L}$$

Informative if r_L is “large enough”

$$\Pr\{e_k^T P e_k > r_L\} = 1 - \Pr\{e_k^T P e_k \leq r_L\}$$

Weighted Bound on the Error

We take into account both **saturated** and **unsaturated** contractive behaviors by weighing their contributions using $\Pr\{e_k^T Pe_k \leq r_L\}$.

Effective Contraction Rate

If the ellipsoidal region of linearity has a “large enough” scaling

$$r_L \geq \frac{1}{1 - \lambda} \text{tr}(PW), \quad \begin{matrix} \text{lim of } \mathbb{E}[e_k^T Pe_k], \\ k \rightarrow \infty \end{matrix} \quad \text{“strong” condition}$$

then,

$$\mathbb{E}[e_{k+1}^T Pe_{k+1}] \leq \bar{\lambda} \mathbb{E}[e_k^T Pe_k] + \text{tr}(PW),$$

for all $k \in \mathbb{N}$ where $\bar{\lambda}$ satisfies,

$$\frac{1}{1 - \bar{\lambda}} \text{tr}(PW) = \frac{\bar{\lambda} - \lambda_L}{\bar{\lambda} - \lambda_U} r_L.$$

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then,

$$\mathbb{E}[e_{k+1}^T Pe_{k+1}] \leq \bar{\lambda} \mathbb{E}[e_k^T Pe_k] + \operatorname{tr}(PW), \quad \Rightarrow \text{compute PRS, PUB}$$

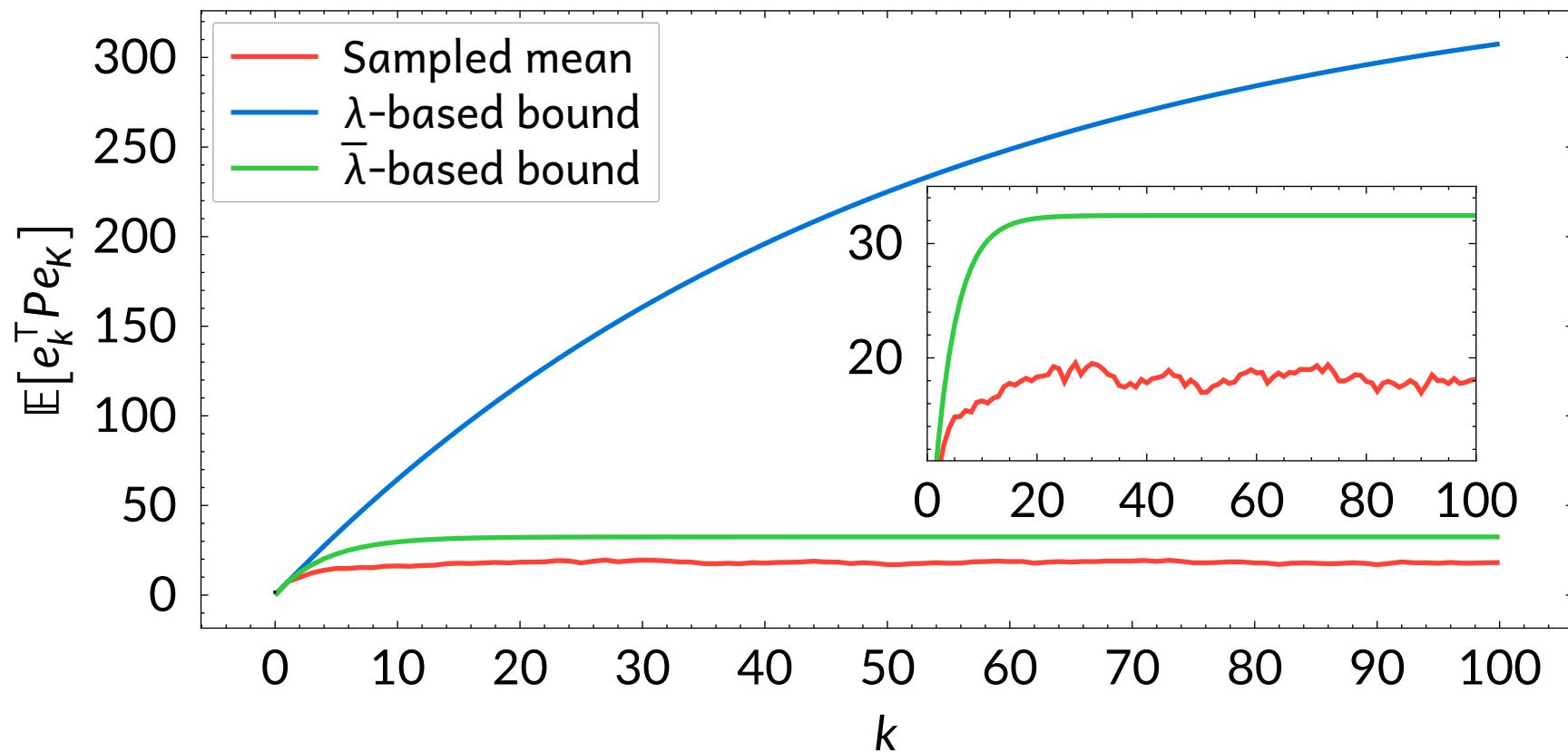
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$$\frac{1}{1 - \bar{\lambda}} \operatorname{tr}(PW) = \frac{\bar{\lambda} - \lambda_L}{\bar{\lambda} - \lambda_U} r_L. \quad \Rightarrow \text{quadratic equation with 1 admissible solution}$$

Tightness of the New Bound

The improvement can be first noticed on the tightness of the expectation bound.

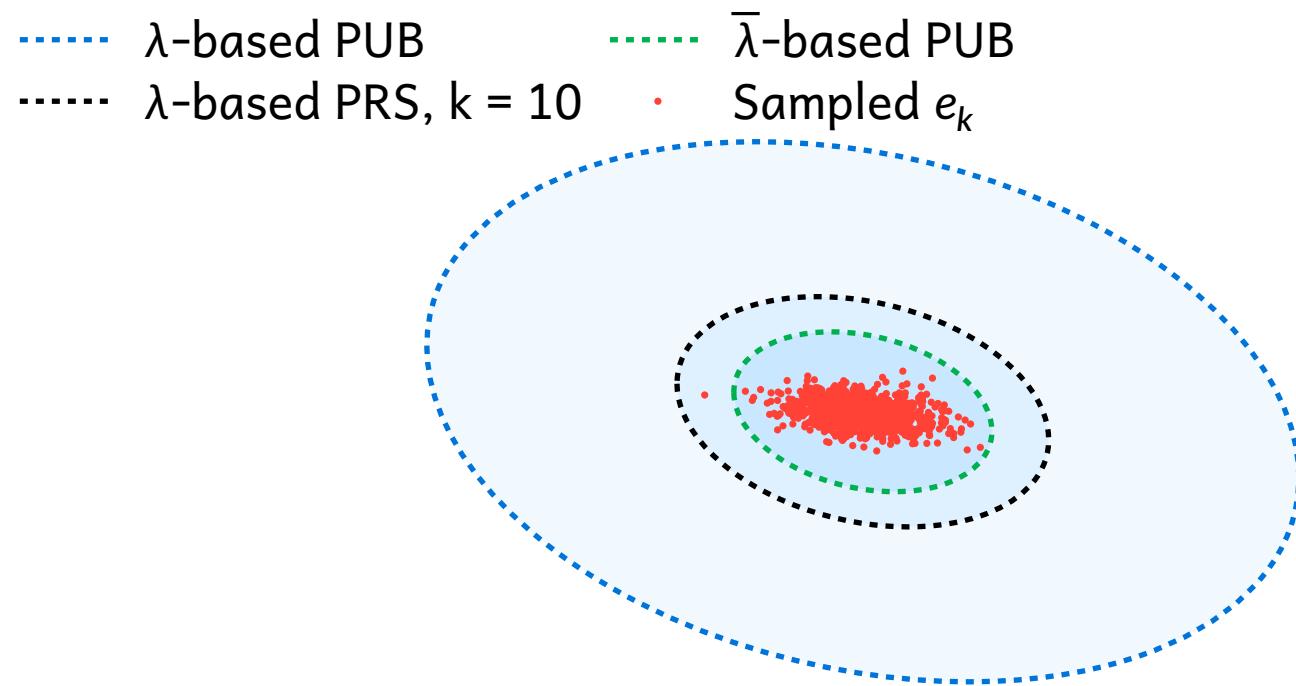
$$\lambda = 0.9802, \bar{\lambda} = 0.7826, \varepsilon_x = 0.2, W = I_2.$$



Tightness of the New Bound

Equivalently, the sets themselves are much tighter. Comparing the **effective PUB** to the **open-loop PUB**.

$$\lambda = 0.9802, \bar{\lambda} = 0.7826, \varepsilon_x = 0.2, W = I_2.$$



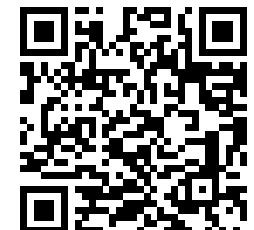
Summary and Outlook

Retracing our steps:

1. We **decouple** the problem through the **generalized sector bound**.
2. We **linearize** the problem through the **polytopic inclusion**.
3. We compute always valid open-loop PRS and PUB using standard methods.
4. We compute tighter PRS and PUB **incorporating linear behavior** under favorable conditions.

Looking ahead:

- Integration into SMPC scheme.
- Further reduction of conservatism using the Moment Sum-of-Squares hierarchy to compute semi-algebraic sets.



Thank You!
